To the Moon or Bust: Do Retail Investors Profit From Social Media-Induced Trading?

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Abstract

This paper provides evidence that social media exacerbates behavioral biases, induces retail trading more than other known traditional attention-grabbing factors, and is detrimental to investor performance. We document that retail investors underperform at both the transaction and portfolio levels from trades placed on days when a stock has abnormally high levels of discussion on social media. Additionally, we investigate the performance of social media investors in other asset classes, such as cryptocurrency, foreign exchange, and commodities, and find that they underperform across all asset classes. These findings are crucial in the context of heightened regulatory scrutiny of retail trading and the ongoing discourse on the role and impact of social media in financial markets.

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"Investing...is a social activity. Investors spend a substantial part of their leisure time discussing investments, reading about investments, or gossiping about others' successes or failures in investing". - Shiller, R.J. 1989.

1 Introduction

Investing has traditionally been a social endeavor, with decisions often shaped by interpersonal relations, peer influence, and collective sentiment. A significant body of academic research highlights peers' pivotal role in guiding investment choices (Shiller and Pound, 1989; Duflo and Saez, 2002; Ouimet and Tate, 2020). Technological advancements and the rise of social media have magnified the interpersonal aspect of investing, transforming how information is generated, disseminated, and absorbed (Miller and Skinner, 2015). Retail traders are progressively turning to social media for insights, often sidelining more conventional sources like financial advisors, newspapers, TV programs, and subscription-based data platforms.[1] Stock picking and day trading videos and streams on YouTube, Twitch, TikTok, Instagram, and text-based messaging boards and groups on Twitter, Reddit, Discord, and Facebook have gained significant traction, informing and facilitating the trading activities of many retail traders.

While several recent studies have found that social media content predicts returns and earnings (e.g., Chen et al. (2014); Bartov et al. (2018); Blankespoor et al. (2014)), there is a growing concern among regulators and academics regarding the impact of social media on retail traders' performance. In the aftermath of the Gamestop short squeeze and meme-stock incidents in 2021-2022, regulators have been expressing concerns about social media potentially hindering market efficiency and exacerbating the performance of retail investors. For example, in December 2022, the Securities and Exchange Commission (SEC) charged

[1] A survey by brokerage firm M1 Finance found that approximately 60% of Gen Z and millennial retail investors made investment decisions based on social media, compared to 25% of Gen X investors and 7% of baby boomer investors. Similarly, Fidelity reported that 41% of its younger investors seek advice from social media influencers. Nasdaq documented that 74% of Gen Zers and 67% of baby boomers used social media to make investment decisions.

several finance influencers for promoting themselves as successful traders and cultivating millions of followers on such platforms as Twitter and Discord.[2] The latest example of social media's effect on markets - the collapse of Silicon Valley Bank (SVB) in March of 2023, has been called the first "social media, internet-based bank run" in U.S. history by policymakers.[3] While the causes of the collapse of SVB are different, discussions and chatters in social media networks have contributed to market anxiety and amplified psychological behaviors behind a bank run (Cookson et al., 2023).

In this paper, we investigate the impact of social media on retail trading and the consequences of this relationship on investor performance at both individual transaction and investor portfolio levels. We empirically examine this question by monitoring the entire chain of social media activity, combining it with retail investor trade logs, and tracing transaction and investor performance. To measure stock-specific social media activity, we focus on Reddit's WallStreetBets (r/WSB) forum, one of the most active and popular social media platforms where users express their views on stock prices and discuss trading strategies. We developed a stock-specific social media activity measure that captures unusual levels of discussions on social media on a given day relative to a benchmark period. We do this by dividing the number of mentions about a specific stock on each trading day by the average number of its mentions over the past 42 trading days. We then split stocks into quintiles based on this measure and define any transaction involving a particular stock as social media-induced if it falls into the top quintile.

To access investor trading records, we use proprietary data from a global trading platform (the Platform, herein), which serves over 25 million registered users from 140+ countries and covers over 2,500 stocks. The Platform allows us to observe individual-level retail trading history, portfolio-level returns, and trader information obtained from Know Your Customer (KYC) answers. Unlike Robinhood, which is more commonly used in previous studies, traders on this platform can take long and short positions and leverage their trades.

[2]https://www.sec.gov/news/press-release/2022-221

[3]Testimonies of Federal Reserve Board Vice Chair for Supervision Michael S. Barr and FDIC chair Martin Gruenberg at a Senate Banking, Housing, and Urban Affairs Committee hearing on "Recent Bank Failures and the Federal Regulatory Response." March 28, 2023.

We begin by examining the degree to which retail investors' trading decisions are influenced by discussions on social media and how this form of trading stands in relation to other attention-driven trading behaviors. Building upon the findings of Barber and Odean (2008), which highlighted the significant impact of attention-catching events on individual investor actions, we analyze the open-close trading imbalance of stocks categorized by trading volume, one-day returns, news coverage, and social media mentions. Our sorting analysis reveals that stocks in the top quintile are traded almost four times as frequently as those in the bottom quintile and those not mentioned on social media. Furthermore, our regression results indicate that a unit increase in social media activity correlates with a more pronounced shift in retail trading than comparable unit increases in other attention-driven trading indicators. Collectively, these findings underscore the paramount influence of social media discussions on retail trading, overshadowing the effects of traditional news, momentum, or trading volumes.

Turning to our main analysis, we study the performance of retail investors from social media-induced trading. First, we find that returns to social media-induced trades are, on average, 1.6-2.8% lower than returns on all other positions opened on the same day. Next, we find that the share of social media-induced trades in investors' portfolios is negatively associated with annualized portfolio returns by 1.7-2.8%.

We attribute the underperformance of attention-based trading to poor market timing and the disposition effect. First, we find that retail investors predominantly trade on days when stocks exhibit abnormally high social media activity, which in turn yields poorer returns. This is consistent with the results of Barber et al. (2021), who found that retail investors incur losses on trades made during periods of high retail order imbalance and trading volume. We show that social media is a contributing factor. This underperformance is compounded by factors such as a short holding period, use of leverage, and frequent trading. Second, we find evidence for the presence of the disposition effect, which is the tendency of retail traders to sell stocks when they are experiencing gains while holding onto stocks when they are incurring losses.

We provide additional evidence that social media investors perform worse in their trades involving foreign exchange currencies, cryptocurrencies, and commodities. Finally, we shed light on heterogeneity among investors, as evidenced by their varying trading behavior and answers to KYC questions. We find that, on average, these investors tend to be younger, male, have less trading experience, have less financial knowledge, exhibit short-term trading strategies, and prefer risk-taking.

Our findings are robust to various measurement choices and regression specifications. First, we repeat our primary analysis by using social media activity measure from Refinitiv's MarketPsych Analytics (RMA), which collects data from over 2,000 selected social media sources such as Twitter, StockTwits, Reddit, Investing.com, and other relevant blogs and forums. Consistently, our results hold, underscoring that our findings are not driven primarily by data selection. Second, our findings remain robust when we employ alternative definitions of our primary variables. Third, our tight fixed effects specifications ensure that attention-grabbing factors and retail trading are not confounded by individual characteristics of investors, specific events on particular days, or inherent characteristics of individual stocks.

The contribution of this paper is threefold. First, our work contributes to the growing body of literature examining the role of social media in capital markets. On the one hand, several studies have shown that social media may positively impact capital markets by facilitating the dissemination of information. For example, Chen et al. (2014) discovered that the content of SeekingAlpha, the fraction of negative words in articles, and the fraction of negative words in comments all have a negative predictive relationship with stock returns. Bartov et al. (2018) used Twitter data to discover that the aggregate opinion of individual tweets can predict a firm's quarterly earnings and announcement returns. Additionally, Blankespoor et al. (2014) found that firms' news dissemination via their Twitter accounts is associated with lower abnormal bid-ask. However, despite these positive aspects of social media, it also presents various risks and challenges. On the other hand, however, discussions on social media platforms can lead to inefficient information processing (Bradley et al., 2021), and amplifies behavioral biases such as the disposition effect and persuasion bias (Chang et al., 2016a; Heimer, 2016; DeMarzo et al., 2003). Additionally, social media can foster uninformed trading by spreading false information (i.e. "fake news"), rumors, incorrect beliefs, and naive trading strategies, leading to "pump and dump" strategies and trading frenzies (Pedersen, 2022). The growing reliance of retail investors on social media for trading generates incentives for disseminating misleading and false information for price manipulation purposes (Farrell et al., 2022). We contribute to this literature by showing that social media harms retail investors' performance.

Second, our study is closely aligned with previous research on attention-induced retail trading behavior, which posits that information processing is costly and capacity-constrained investors tend to purchase stocks that have first captured their attention. Such attention-motivated buying results in concentration on stocks that receive investors' attention, resulting in poor returns. Barber and Odean (2008) documented three proxies of attention-grabbing events: media coverage, unusual trading volume, and extreme past-day returns. This attention model predicts lower returns, and Barber et al. (2022) recently showed that stocks with the most significant increase in users on the popular Robinhood app tend to have poor returns. Previous studies have also demonstrated stock price reversals following attention-grabbing events, such as Jim Kramer's stock recommendations (Engelberg et al. (2012)), the WSJ Dartboard Column (Liang (1999); Barber and Loeffler (1993)), Google stock searches (Da et al. (2011); Da, Hua, Hung, and Peng (Da et al.)), and repeat news stories (Tetlock (2011)), which indicate that individual investors overreact to stale information, leading to temporary movements in stock prices. Our study extends existing findings by demonstrating that retail trading, measured by both open-close imbalances and the log number of open trades, increases on days of heightened activity on the social media platform. Barber et al. (2021) have reconciled two conflicting empirical findings in the literature that retail traders underperform in the short-term, and retail trading activity, as proxied by order imbalance, has positive predictability for short-term stock returns. The authors argue that retail trading is driven by attention-grabbing events, consistent with the theoretical prediction that retail investors are net buyers when stocks catch their attention, resulting in temporary price increases. Our study further shows that although social media activity, i.e., the level of discussions, positively predicts both aggregate retail trading volume and short-term stock returns, retail traders still lose money when engaging in such trading activity. We attribute this outcome to factors such as market timing and behavioral biases such as the disposition effect.

Finally, this paper relates to the literature on herding behavior, which refers to the phenomenon where investors copy each other's actions or make decisions based on the actions of others, influenced by both information and behavior (Shleifer and Summers, 1990; Nofsinger and Sias, 1999; Sias, 2004). Information-driven herding behavior suggests that investors make similar investment choices when they face similar information environments. For instance, Shiller et al. (1984) and De Long et al. (1990) argue that individual investors are susceptible to the influence of fads and fashion. Shleifer and Summers (1990) also contend that retail investors tend to herd when they follow similar signals, such as brokerage house recommendations, popular market influencers, and forecasters. Conversely, behavior-driven herding behavior is linked to psychological biases, such as the representativeness heuristic and disposition effect, and attention-grabbing events (Barber et al., 2009; Merli and Roger, 2014). We contribute to this literature by documenting that discussions on social media platforms can lead to herding behavior by retail investors.

The findings of this study are of significant importance in the context of heightened regulatory scrutiny of retail trading and ongoing discussions about the impact of social media networks on capital markets. This paper makes a contribution by demonstrating that retail investors underperform in social media-driven trading due to late market entry and holding onto losing positions as prices predictably decrease over time.

The structure of the paper is as follows: Section 2 presents the data, sources, sample construction, and measurement of key variables. Section 3 presents the main findings of the study. Section 4 investigates the underlying mechanisms. The paper concludes in Section 5.

2 Data and Key Variables

The following section outlines the data sources and details of constructing key variables. Furthermore, we present descriptive results on social media activity, the characteristics of firms and investors, and key empirical findings.

2.1 Social Media Activity

2.1.1 Reddit

Reddit is a social media network platform that contains online communities, also known as subreddits, that are focused on specific topics, such as politics, humorous memes, sports teams, or computer games, among numerous others. One such subforum, r/WSB, was created in 2012. It describes itself as "a community for making money and being amused while doing it." It is primarily used for post-investment advice, stock price expectations, comments on individual trades, and sharing speculative trading strategies. r/WSB had profoundly affected several specific stock trading frenzies, the most prominent in the January 2021 GameStop's short squeeze. r/WSB reached 11.8 million subscribers as of March 2022 (see Figure 1).

While r/WSB has several subforums where users communicate, this paper focuses on two subforums: "Tomorrow's Moves" and "Daily Discussion." Each trading day, moderators of r/WSB create a "Tomorrow's Moves" thread with a date, where users discuss what stocks they are trading the next trading day. In another daily dated subforum, "Daily Discussion," users discuss the current day's trading session and comment on specific stocks (see Figure A1). By including a "cashtag" - a dollar sign ($) followed by a stock's ticker symbol, r/WSB users can specify that their comment refers to a specific stock. We obtained our dataset from a third-party provider, which scraped all posts and comments from the "Tomorrow's Moves" and "Daily Discussion" subforums of Reddit's r/WSB. The data covers the period from January 1st, 2019, to September 30, 2021[4].

[4]This data is used by the provider for analytics and visualization purposes and is sold on a subscription basis

Table 1 displays a selection of typical comments, and Table 2 provides a summary of statistics of stock-specific mentions r/WSB for the period between 2019Q1 and 2021Q3. The r/WSB sample includes 4,006,825 comments for 5,822 assets[5]. On average, comments in r/WSB have bullish sentiments, as evidenced by an average sentiment score of 0.064. The activity of users in r/WSB is concentrated during trading days and hours, as depicted in Figure A2, which shows the distribution of posted comments by day of the week and hour of the day. Table 3 illustrates the top 20 stocks with the highest cumulative number of mentions in RMA and comments in r/WSB samples during the study period.

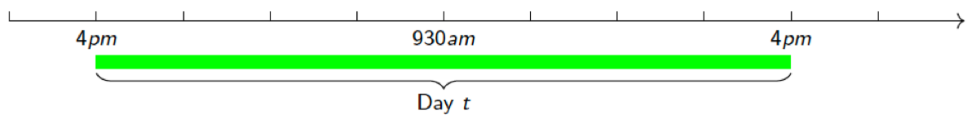
2.1.2 Measurement

In this study, we construct firm-specific social media activity variables by focusing on the abnormal volume of mentions on the day t relative to a benchmark period. Subsequently, we sort stocks into quintiles based on the abnormal daily volume of mentions to accurately identify the stocks with elevated levels of social media discussions that likely attract investor attention.

First, to measure social media activity in r/WSB, we follow Cookson and Niessner (2020) and assign comments on stock s posted between the close of the previous trading day $(t-1)$ and the close of the current trading day (t). We also consider comments posted after 4:00 PM on day t, which are assigned to the next day $(t+1)$ (as illustrated in the figure below). Thus, the total number of comments for stock s on the day t includes all comments posted between 4 PM on the previous trading day and 4:00 PM on day t. Additionally, we calculate a second version of social media activity by summing up comments posted between 4 PM on day $t-1$ and 9:30 AM on day t to capture only overnight social media activity, which is helpful for tests that exploit the timing of comments.

Next, we evaluate the deviation of the daily number of mentions of a stock s in r/WSB from its average number of mentions over the preceding trading days between $t-47$ to $t-6$ (excluding the preceding five trading days). Abnormal social media activity for a stock s on

[5] r/WSB sample covers all assets, including ETFs. In our main analyses throughout the paper, we restrict the r/WSB sample to only stocks, defined as shrcd=10 from CRSP



the day t is defined as:

$$Abnormal\ Social\ Media\ Activity_{s,t} = \frac{Mentions_{s,t}}{Average\ Mentions_{s,[t-47;t-6]}} \quad (1)$$

Lastly, on the day t, we sort all stocks into quintiles based on their abnormal social media activity. We then define the binary variable $SocialMediaInducedTrade$ as one if the stock's abnormal social media activity falls within the top quintile and zero otherwise.

2.2 Retail Trading Activity: the Platform

We obtain proprietary data from a multi-asset global online trading platform (”the Platform”) that allows users to trade individual stocks, exchange-traded funds, stock indices, foreign currencies, commodities, and cryptocurrencies. It has more than 25 million registered users in over 140 countries with a coverage of over 2,500 assets. The Platform's users can trade over 2,500 assets, take long or short positions, and use leverage to support their trades. Concerning stock trading, the Platform supports trading across 17 exchanges around the world. This project focuses solely on equity trades conducted in the NYSE and Nasdaq exchanges. Our datasets include the Platform's complete trade log, portfolio-level returns, and trader characteristic data with information on each trader's country of residence, gender, and age, as well as answers to KYC questions on prior trading experience, knowledge in trading, preferred trading strategy, the primary purpose of trading, attitude towards risk, trading frequency, net annual income, total cash, and liquid assets, sources of income, occupation, and more. The Platform has recorded 53,726,331 transactions in NYSE and NASDAQ exchanges between January 1, 2019 - March 31, 2021.

Table 4 presents a summary of the characteristics of traders on the Platform based on their observed trading history and answers to Know-Your-Customer questions. We define social-media-induced traders as follows: first, we restrict our sample to only those users who traded at least once on U.S. exchanges during the sample period. Second, we calculate the share of social media-induced trades in the sample period by summing all trades across all asset classes and dividing by the total number of trades. Finally, traders are classified as "Social Media-Induced Traders" if their ratio of social media-induced trades to all trades is in the top 20th percentile among all traders. Table 4 shows that compared to regular retail traders, social-media-induced traders are, on average younger, male, have less trading education and experience, and exhibit a preference for short-term returns with high risk-reward ratios.

2.3 Other Datasets

We use several other datasets in this paper. We obtain stocks' coverage in traditional news outlets in RMA dataset from Refinitiv. RMA dataset also contains stocks' social media coverage, which we use in the robustness tests. Firm-specific fundamentals are obtained from Compustat, asset, and index prices from CRSP. To capture the total retail trading volume in US markets, we obtain the Retail Trading Activity Tracker dataset that tracks individual investors' trades according to classification by Boehmer et al. (2021). We define $RetailShare$ as a continuous variable that ranges from 0 to 1 and represents the ratio of $USD traded by retail investors in a given ticker divided by the total $USD traded by retail investors across all tickers.

3 Results

This section presents the main results. We first explore the extent to which individuals trade based on social media discussion and how this type of trading compares to other attention-driven trading. We further study the performance of retail traders and explore potential mechanisms contributing to these results.

3.1 Attention Induced Factors and Retail Trading

Sorting Analysis

We categorize stocks into deciles based on the lagged abnormal trading volume and past-day absolute returns. Subsequently, we determine the number of opened and closed trades for all stocks in each decile for a given day, t. Finally, we calculate the open-close retail trading imbalance for each decile for each date t using the following formula:

$$Open\,Close\,Imbalance = \frac{\sum Open\,Trades - \sum Close\,Trades}{\sum Open\,Trades + \sum Close\,Trades} \tag{2}$$

The results are presented in Table 5. They align with prior literature, demonstrating that individual investors exhibit attention-driven trading behavior on days with high trading volume, days following extreme one-day returns, and when stocks are in the news. Column 1 displays the open-close imbalance for stocks sorted based on the previous day's returns. Following Barber and Odean (2008), we observe that stocks in the lowest decile of negative returns of the previous day (first decile) receive the highest level of retail investor trading (open-close imbalance is 6.69). The open-close imbalance decreases to 2.19 for stocks in the ninth decile and increases to 2.96 for stocks with the best past-day return performance. Column 2 presents the open-close imbalances for stocks sorted based on the previous day's abnormal trading volume. Our findings suggest that stocks with high abnormal trading volume attract more retail investors' trading, and the open-close imbalance rises steadily from 1.34 (lowest decile) to 6.74 (highest decile).

We sorted the open-close imbalances into five quintiles by stocks' social media mentions and news mentions in RMA. Column 3 of Table 5 suggests that retail investors' likelihood of opening a position on stocks rises with the abnormally high news coverage of the stocks. Stocks with the lowest mentions in the news have an open-close imbalance of 3.58, while stocks in the top quintile have an open-close imbalance of 7.16.

The results for our primary variable of interest, social media-induced trading, are presented in the last columns of Table 5. The table indicates that retail investors trade more stocks with abnormally high social media activity levels than other stocks. Stocks in the top quintile receive nearly four times more trading than stocks in the lowest quintile.

Regression Analysis

To further examine the relationship between attention-grabbing factors and retail trading, we move beyond the descriptive findings and estimate a linear probability model by regressing retail trading activity on four attention-inducing factors in both bivariate and multivariate models:

$$RetailTrading_{s,t} = \beta_1 SocialMedia_{s,t} + \beta_2 News_{s,t} + \beta_3 TradingVolume_{s,t} + \beta_4 Return_{s,t} \quad (3)$$

In the model, the dependent variable denoted by $RetailTrading_{s,t}$ is represented by either the natural logarithm of the total number of open trades for stock s on the day t or by open-close imbalance. The independent variable of social media activity, $SocialMedia_{s,t}$, is an indicator variable equal to one if the stock's abnormal level of mentions or comments falls in the top 20% of the day t, and zero otherwise. Other independent variables are defined similarly and described in Appendix A. The model includes stock and date fixed effects.

In Table 6, the results from estimating Equation (3) for the open-close imbalance and the logarithm of the number of open positions are presented in Panels A and Panel B, respectively. The first four columns showcase the results from bivariate regressions, while the last column presents the results from multivariate regression. The findings reinforce previous observations from the sorting analysis, demonstrating that stocks with abnormally high volumes of social media discussions tend to have more significant retail trading activity, as measured by the open-close imbalance and the logarithm of the number of open positions. Notably, social media has a more significant impact on retail trading than any other attention-inducing factors.

To address concerns over the external validity of our findings, which are based on individual user trading records on the platform, we conducted a similar analysis using different dependent variables, which captures the total retail trading volume of stocks in US markets. The results, as presented in Table 7, suggest that there is a positive association between retail trading volume and stocks being in the top quintile of social media activity on a given day, with this association being more substantial than the relationship between abnormal news coverage and retail trading. Regardless of the specification, trading volume variable, social media activity measurement sample, or control variable definitions, our analysis consistently shows that information in social media has a greater impact on retail trading than other known attention-grabbing factors. To conclude this section, we have documented that retail investors tend to trade stocks that have recently gained their attention and that stock-specific discussions in social media serve as an additional source of attention.

3.2 Social Media Activity and Investor Returns

This section investigates the impact of attention-based trading driven by social media signals on investor performance. Our findings from the previous sections indicate that retail investors trade stocks that have recently captured their attention through abnormal trading volume, past extreme returns, abnormal news coverage, and abnormal social media activity. If these signals hold firm-specific and value-relevant information, and retail investors can correctly process them, we expect to see improved performance at both the individual trade and portfolio levels. Conversely, we anticipate observing subpar performance if these signals lack value-relevant information, contain misleading or noisy signals, or if retail investors cannot process them correctly. To examine this, we employ two methods. First, we perform investor-date-transaction level regressions to assess the performance of retail investors from trades prompted by social media compared to other trades. Second, we analyze the annualized portfolio returns of retail investors through cross-sectional regressions to determine the performance of social media-triggered trades within their portfolios.

3.2.1 Evidence from Trade-Level Returns

To evaluate the performance of social-media-induced trades versus non-social-media-induced trades by retail investors, we estimate the following baseline regression specification:

$$
\begin{aligned}
Return_{i,s,t} = \beta_1 Social\ Media\ Trade_{s,t} + \beta_2 News_{s,t} + \beta_3 Trading\ Volume_{s,t} + \\
+ \beta_4 Return_{s,t} + \lambda_t + \mu_s + \gamma_i \quad (4)
\end{aligned}
$$

The trade-level return, $Return_{i,s,t}$, is measured for stock s placed on the day t by investor i. The $SocialMediaTrade_{s,t}$ variable takes three forms. First, as an indicator variable that is equal to 1 if the abnormal volume of mentions in r/WSB for stock s on the day t falls in the top quintile among all stocks and 0 otherwise. Second, as the logarithm of the number of mentions. Third, as an indicator variable that captures comments only between after-market hours on the day $t-1$ and pre-market hours on the day t. The model includes the date, stock, and investor fixed effects represented by λ_t, μ_s, and γ_i, respectively.

Table 8 presents the results. The results demonstrate a statistically significant and economically meaningful association between social media-induced trading and trade-level returns. Specifically, trades executed on days with abnormally high social media activity for a given stock result in lower returns than other equity trades. On average, positions opened on stocks with high abnormal coverage in r/WSB forums underperform other stocks by 1.6% to 2.8%. The short holding period, leveraged and short positions further exacerbate this negative impact on the performance of social-media-induced trades.

3.2.2 Evidence from Portfolio Returns

Following the documentation of inferior performance of trades induced by social media, we evaluate the overall portfolio performance of investors who systematically trade based on social media signals from both r/WSB and broader social media platforms. To accomplish this, we estimate a cross-sectional regression as follows:

$$Return_i = \beta_1 Social\,Media\,Trade\,(\%) + \beta_2 Positions\,(log) + \beta_3 Trading\,Months\,(log) + \\ + \beta_4 \overrightarrow{Asset\,Classes\,(\%)} + \beta_5 Leveraged\,Positions\,(\%) + \beta_6 Short\,Positions\,(\%) + \\ + \beta_7 Gender + \beta_8 Age + \beta_9 Trading\,Knowledge \quad (5)$$

$Return_i$ represents the annualized and market-adjusted monthly portfolio returns of trader i for all trades across all stock classes over the sample period. The main variable of interest, $SocialMediaTrade(\%)$, represents the share of social media-induced trades by trader i from all their equity trades placed in the corresponding exchanges during the sample period. The specification also controls for the total number of trades by an investor, the number of active trading months, leverage, short positions, and trading behavior in other exchanges, such as crypto, commodities, indices, and foreign exchange. The regression also includes investor-level characteristics, such as gender, age, and trading knowledge, which are derived from KYC questions and measured as an indicator variable equal to one if the investor has the relevant trading experience, attended trading courses or holds a relevant degree, and zero otherwise. Additionally, we control for country-specific differences between traders by including a country-fixed effect in column 3, which can account for any differences in the financial literacy of investors across countries. The results are reported in Table 9 and show that a higher proportion of social media trades in an investors' portfolio is associated with a negative annualized portfolio return. The return ranges from -2.8% to -1.7%.

4 Mechanism and Additional Tests

The results so far indicate that social media-induced trades negatively impact retail investors' performance. In this section, we examine a few potential causes of this phenomenon. Retail investors tend to make performance-reducing trades due to their lack of realization of being at an informational disadvantage and/or overconfidence in their trading abilities (Odean, 1998, 1999; Barber and Odean, 2000). When stocks attract attention, retail investors tend to be net buyers, leading to price increases followed by reversals. With its absence of traditional oversight and potential for misinformation, social media provides an avenue for retail investors to disseminate their interpretations of firm-specific information or disclosures. However, the question remains, do all retail investors act similarly in response to social media signals and exhibit similar suboptimal trading performance?

4.1 Market Timing

4.1.1 When Retail Investors Trade?

The widespread reach of information exacerbates persuasion bias among investors, who need to adjust their assessment of information validity based on repetition properly (DeMarzo et al., 2003).

We hypothesize that most retail investors are late entrants to the market and make trades based on stocks they discover on social media. Consistent with Barber et al. (2021), which documented that the losses incurred by day traders are predominantly concentrated in stocks with high retail order imbalance and abnormal trading volume, we expect that most retail trading activity on a specific stock to be concentrated during periods of elevated social media activity. However, the theoretical predictions of Pedersen (2022) posit that short-term rational investors can identify signals about a firm and observe the formation of beliefs on social media, thereby capitalizing on market bubbles for short-term profits. In our setting, we explore whether social-media-induced trading can have episodes of positive returns and whether short-term rational investors can generate positive excess returns before the bubble's peak.

To validate these hypotheses, we carry out an event-study analysis at the individual trade level and run 21 separate regression analyses using the following specifications:

$$Return_{i,s,t} = \beta_1 Social\ Media\ Trade_{t-x} + \beta_n Trade\ Level\ Controls + \lambda_t + \mu_s \tag{6}$$

where, $Return_{i,s,t}$ represents trade-level returns for stock s traded on day t by investor

i. The key variable of interest is $SocialMediaTrade_{t-x}$, which is one of 21 time-indicator variables indicating the days relative to the day when a stock experiences abnormal social media activity in the top 20%. For instance, the coefficient of $SocialMediaTrade_{t-10}$ reflects the average difference in returns between trades for stocks with abnormally high social media activity ten days after and all other equity trades. Similarly, $SocialMediaTrade_{t+2}$ represents the average return difference between trades for stocks with abnormally high social media activity two days before and all other equity trades.

Panel A of Figure 2 displays the results of 21 regressions computed by estimating equation (6). The figure illustrates that stocks that experience significant levels of discussions on social media present different returns depending on the day a retail investor trades them. In the [-10; +10] window surrounding the peak of social media activity on the day $t = 0$, the average returns generated by social media-induced trades are positive and statistically significant up to five days before day $t = 0$. This suggests that rational short-term retail investors can profit from social media-induced trades if they execute them at least five days before the stock reaches its peak social media activity. However, returns become negative from day $t = 0$, when social media activity is at its highest for the stock, supporting the hypothesis and theoretical predictions put forth by Pedersen (2022)'s model that naive retail investors tend to enter the market too late when price bubbles are about to collapse, and returns are reversing. Most importantly, the negative returns documented in Table 8 are mainly concentrated on trades initiated one day before or after the day when the social media activity for the stock exhibits high abnormal volumes.

Similarly, to examine the hypothesis that retail trading volume is highest on days when stocks have abnormally high social media activity, we repeat the specification presented in equation (6) by replacing the dependent variable with $Trades_{i,s,t}$. This variable represents the natural log of the number of open buy trades for stock s traded by investor i on day t. We run 21 separate regressions to analyze this relationship.

$$Trades_{i,s,t} = \beta_1 Social\ Media\ Trade_{t-x} + \beta_n Trade\ Level\ Controls + \lambda_t + \mu_s \tag{7}$$

Panel B of Figure 2 shows the results. This figure displays the relationship between the difference in trade volumes and the proximity to a day with abnormally high levels of social media activity ($t = 0$). The coefficients indicate a marked increase in stock trading by retail investors when a stock experiences abnormally high levels of discussion on social media.

4.1.2 Does Social Media Predict Returns?

Next, we examine the performance of a trading strategy that sorts stocks based on abnormal social media activity on day 0, and tracks returns over a prolonged horizon. The stocks are sorted into two groups, the bottom 20% and top 20%, with abnormal social media activity, as computed by equation (1). The market-adjusted returns are computed as the difference between daily stock returns and the value-weighted CRSP return. The cumulative market-adjusted returns, weighted by market capitalization, are then calculated for each quintile of stocks. Figure 3 illustrates the results. It displays the returns for 150 days from when stocks with the highest (red line) and the lowest (blue line) abnormal social media activity are sorted. The figure indicates that stocks with the highest abnormal social media activity exhibit inferior performance over time compared to stocks with the lowest abnormal social media activity.

Next, to validate our findings and to further investigate the trajectory of market-adjusted future returns for social media-induced trades, we estimate a panel regression of the following form:

$$Return_{s,t+x} = \beta_1 Social\,Media\,Trade + \beta_2 News + \beta_3 Past\ Returns + \\ + \beta_4 Trading\,Volume + \lambda_t + \mu_s + \gamma_t \quad (8)$$

The dependent variable is the return of a stock s on the day $t + x$. Table 10 presents the results and shows that controlling for the past news, trading volume, and past returns, the social media activity negatively and statistically significantly predicts market-adjusted returns for at least up to a month if measured by a broader set of social media networks and at least six months. Although social media-induced trades exhibit positive returns on the day of a trade, they reverse the next day entirely and decrease over time. Tests in this section illustrate that stocks that have high levels of discussions in social media perform worse compared to other trades. Taken together with earlier evidence from actual retail trades, we show that retail investors are worse off by trading such predictably performance-worsening stocks.

4.2 Disposition Effect

Another driving force behind the persistent losses experienced by retail investors from trades influenced by social media may be attributed to the disposition effect, which is one of the most well-established findings in the study of individual trading behavior is the disposition effect (Kahneman and Tversky, 1979; Barberis and Xiong, 2012; Ingersoll and Jin, 2013). Retail traders tend to sell stocks when they are experiencing gains while holding onto stocks when they are incurring losses. We hypothesize that social media networks have amplified this behavioral bias, particularly as retail investors are susceptible to forming the belief that they are part of a more significant movement or narrative and tend to follow allegedly profitable trading strategies promoted on social media. One such expression on Reddit is "diamond hands," an investment strategy in social media. This term, often depicted in emoji form, refers to an investor with a high-risk tolerance for high-volatility stocks who hold onto their investment even under pressure to sell. Another common sentiment expression, "HODL," meaning "hold on for dear life," is frequently seen in investment strategy discussions on social media networks.

To examine the presence of the disposition effect among retail investors on the Platform, we employ the following specification to determine if they have a higher tendency to sell stocks that are experiencing gains compared to those that are incurring losses:

$$Sale_{i,s,t} = \beta_1 Gain + \beta_2 Social\ Media\ Trade_{i,s,t} + \beta_3 Gain \times Social\ Media\ Trade_{i,s,t} \quad (9)$$

Our tests were conducted at the account (i), stock (s), and date (t) level and were restricted to a sample of long equity trades on U.S. exchanges. The variable $Sale_{i,s,t}$ is a dummy indicator equal to 1 if investor i sold stock s on date t, and 0 otherwise. The $Gain$ is another indicator variable equal to 1 if stock s was in a state of gain at the close of date t, and 0 otherwise. The coefficient of $Gain$ measures the increase in the probability of selling a position if it was at a gain rather than at a loss. The interaction term between $SocialMediaTrade_{i,s,t}$ and $Gain$ measures the difference in the disposition effect for stocks with high social media coverage and other stocks. To eliminate the possibility that retail investors' inattention solely drives the results to their accounts rather than deliberate choices to sell, we followed the method in Chang et al. (2016b) and restricted our sample to only those periods (months) in which a retail investor conducted a sale of any security in their account. This ensures that the retail investor was attentive to their portfolio during that period. Table 11 presents the results. The first column shows the results for the full sample, but to eliminate the impact of day trading, which accounts for roughly one-third of trades on the Platform, we exclude these trades from our sample and present the results in column 2. The coefficient of the interaction term is positive and statistically significant. It can be interpreted as indicating that when a retail investor sells some stocks, they are 0.9% more likely to sell a stock if it is at a gain. Columns 3 and 4 present the results when the sample is restricted to only non-leveraged trades and stocks, respectively, and show similar results, confirming the presence of the disposition effect.

4.3 How Do Social Media-Induced Investors Perform With Other Asset Classes?

In the paper's final section, we examine the trading performance of retail investors across various asset classes in the context of their engagement with social media-influenced trading in the equity asset class. It is plausible that investors who trade stocks based on signals and strategies propagated on online forums also exhibit similar trading behavior across other asset classes. Our unique investor trading records data enables us to observe the trading records of retail investors in cryptocurrency, commodities, bonds, and currency markets.

To determine the performance of retail investors in these markets, we compute the returns from each transaction in each of those exchanges. We then divide the sample into five groups for each corresponding asset class and regress trade-level returns on an indicator variable equal to one if the investor is a "Social Media Investor" and zero otherwise. We identify "Social Media Investors" in the same way as defined in Section 2.2. Table 12 presents the results of the regression analysis, which demonstrate that "Social Media Investors" not only perform worse compared to other investors in their stock trades compared to other investors but also exhibit lower performance in foreign exchange currencies, cryptocurrencies, and commodities. Social Media Investors lose, on average, 0.7% in all trades. 0.9% in equities, 1% in crypto, 0.6% in foreign exchange currencies and 1.1% in commodities.

5 Conclusion

The distinct characteristics of social media, such as user-generated content, the lack of peer review, and its speed and reach through network effects, suggest that it can uniquely influence capital markets. With the rise of meme stock investment, this impact has been amplified in recent years, but its influence in the capital markets is a phenomenon that has been around for a while. The SEC raised concerns as early as 2014 about the growing reliance of U.S. investors on social media as a source of information for stock research, investment strategy guidance, current news, and market discussions.[6]

Notably, social media-driven trading is not limited to Reddit, Discord or Twitter and extends to a broader audience. For instance, Facebook hosts numerous private and public groups with hundreds of thousands of members who share, discuss, and exchange information related to stock picking. TikTok, on the other hand, has videos labeled as "stock picks"

[6] https://www.sec.gov/oiea/investor-alerts-bulletins/ia_socialmediafraud.html.
Concerns regarding the impact of social media on capital markets have been echoed globally by securities market regulators. The European Securities and Markets Authority (ESMA) has expressed concern that spreading misleading trading advice via social media is putting investors at risk. Additionally, the International Organization of Securities Commissions (IOSCO) has established the Retail Market Conduct Task Force, identifying the impact of social media on investor behavior as a top concern.

and "Robinhood investors" that collectively receive 4 billion views. Additionally, "traditional" social media platforms such as YouTube and Twitter feature influencers who discuss stocks, live stream their trading sessions, and post their stock recommendations to massive audiences.

The SEC is currently exploring using gamification and behavioral prompts to determine potential actions that can increase investor protection. This examination is crucial, as it impacts retail investors' behavior, market prices, and outcomes of gains and losses. Our paper also investigates how interactions between social media and other key players in financial markets, such as traditional news outlets, analysts, institutional investors, and short sellers, impact the level of discussions regarding a particular stock in social media.

This paper offers important insights into the relationship between social media, retail trading, and investor performance. First, our results indicate that stock discussions on social media platforms significantly impact individual trading decisions more than other attention-grabbing factors. Then, our main results show that retail investors underperform from trades placed when an asset has high abnormal discussions and mentions across all social media platforms. Lastly, our results reveal that social media investors perform worse not only in their equity trades but also in trades involving foreign exchange currencies, cryptocurrencies, and commodities.

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6 Figures

Figure 1. The popularity of r/WSB

This figure illustrates the number of registered users of r/WSB over time. The Y-axis is in millions. Source: Reddit

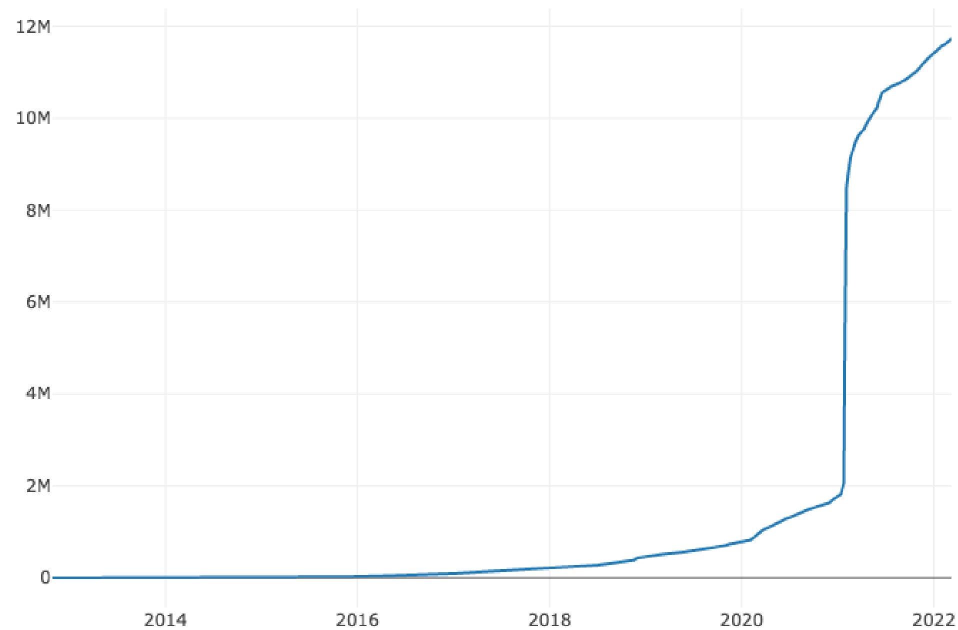
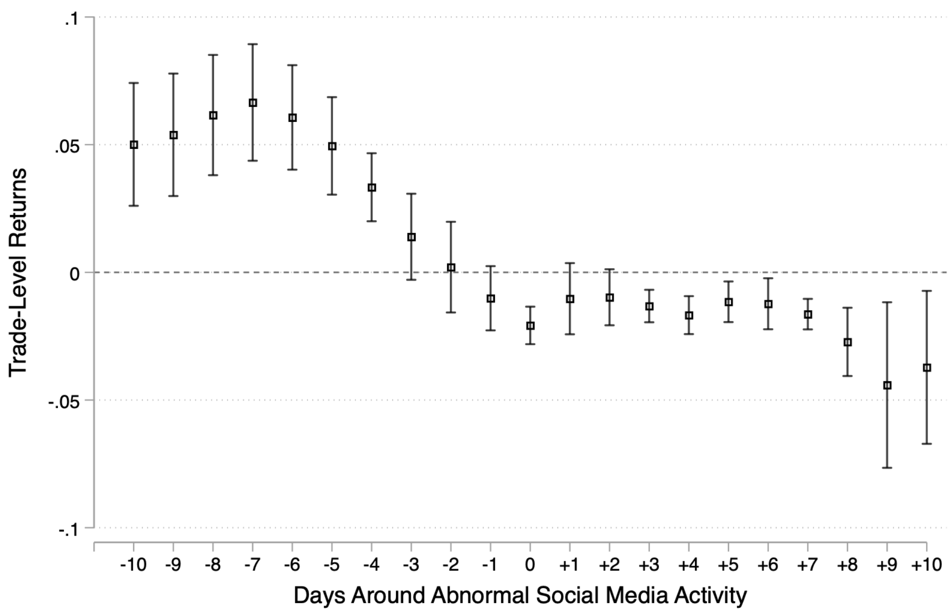


Figure 2. Trade-level Returns of Retail Investors and Social Media: RMA

The figure shows investor trade-level performance and trading behavior around high abnormal social media activity days. Panel A plots the coefficient of the variable of interest from 21 regressions in equation (6), where the dependent variable is trade-level returns. Panel B plots the coefficients of log number of opened positions estimated from equation (7). Each regression has one of the 21-time indicator variables, from $t-10$ to $t+10$, indicating the number of days relative to the day t when the stock was classified as a social media trade, zero otherwise. Figures plot the coefficients from these time indicator variables. For example, the coefficient on the $t-10$ shows the average difference in trading between stocks with abnormally high social media activity in 10 days and all other stocks.

Panel A: Trade-Level Returns



Panel B: Timing of the Trading Behavior of Users in the Platform

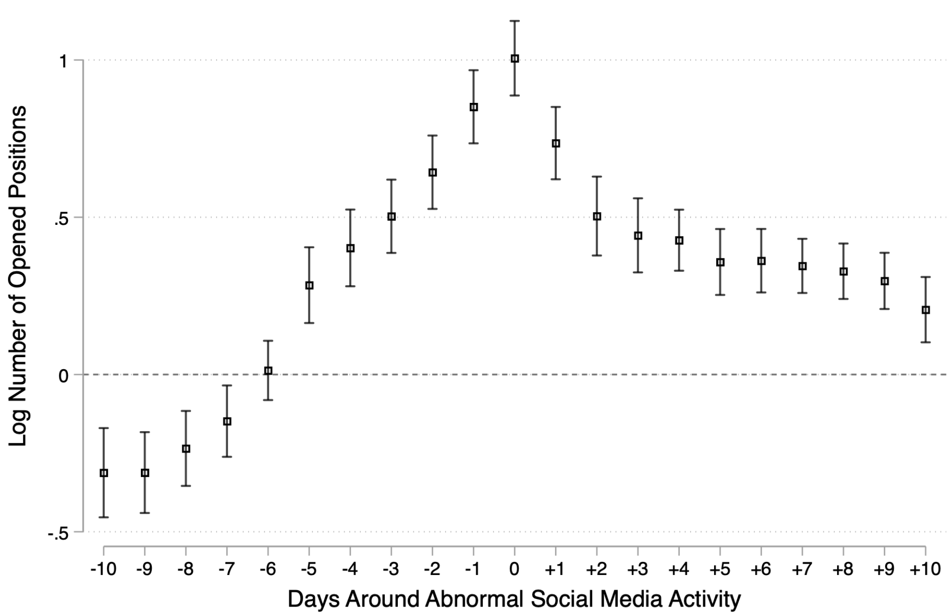
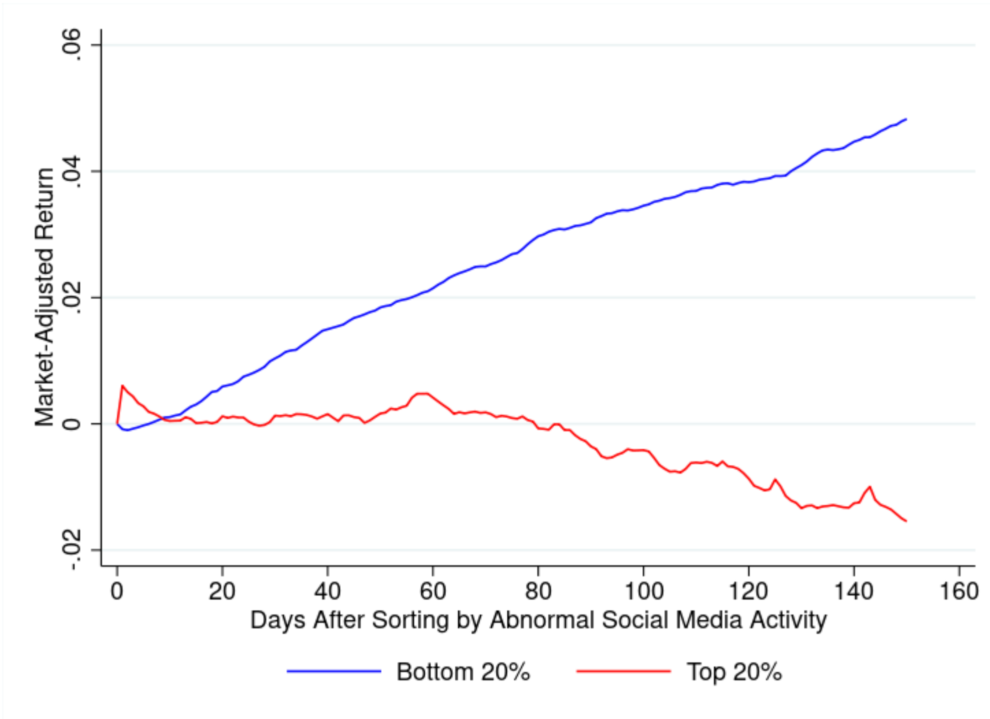


Figure 3. Market-Adjusted Returns of Stocks in Top and Bottom Quintiles by Social Media Activity

The figure depicts the cumulative market-adjusted returns over 150 days after market close on day 0 for stocks in the top and bottom quintiles of abnormal social media activity.



7 Tables

Table 1. r/WSB sample comments

This table illustrates comments posted in "Tomorrow's Moves" and "Daily Discussions" sub-forums of r/WSB between 12:53 - 12:56 pm on March 26, 2021. Column 1 shows the ticker extracted from a comment, column 2 shows the timestamp (EST timezone), and column 3 shows the sentiment score for each comment, calculated by the VADER method. Panel B shows five comments from r/WSB's "Tomorrow's Moves" and "Daily Discussions ."Source: Reddit

Comment	Company	Sentiment score
TSLA earnings call is a joke. So much uncertainty and indirect answers. No reason for the stock price to moon.	Tesla	-0.5506
I bought FB 252.5 puts for like 30$, cant wait to see my gains tomorrow	Facebook	0.5994
Lmaoooo, $MTCH missed across the board and has to pay half their revenue because of a lawsuit and it's still green Lmaoo	Match	-0.5423
$PYPL missed by 2 cents and is -30. Lmaooooooooo	Paypal	-0.296
Time to buy GOOG calls were yesterday but I'll do so today because it will increase a few hundred points after the split	Google	0.4497

Table 2. Summary Statistics of RMA and r/WSB Samples

Panel B: r/WSB sample

	Comments			Stocks	Sentiment Score		Users
	All	Bullish	Bearish	N	Mean	SD	N
Full Sample	4,006,825	1,549,196	1,072,787	5,822	0.064	0.429	9,696,811
By quarters							
2019 Q1	50,267	19,949	15,000	1,198	0.050	0.442	520,542
2019 Q2	66,430	26,717	19,435	1,236	0.058	0.438	583,400
2019 Q3	74,608	28,074	22,453	1,402	0.037	0.435	663,339
2019 Q4	58,936	22,166	17,845	1,372	0.037	0.437	773,269
2020 Q1	245,924	88,424	75,278	2,180	0.024	0.433	1,070,055
2020 Q2	514,205	190,639	149,169	2,990	0.040	0.430	1,308,914
2020 Q3	523,658	194,864	147,475	2,913	0.046	0.425	1,523,676
2020 Q4	530,543	198,494	141,695	2,981	0.054	0.419	1,762,121
2021 Q1	1,010,455	402,972	258,135	3,845	0.078	0.436	9,709,213
2021 Q2	596,720	247,727	139,914	3,626	0.103	0.425	10,620,004
2021 Q3	332,145	128,098	85,519	3,332	0.070	0.420	10,893,421

Panel A: RMA Sample

	Mentions	Stocks	Sentiment Score	
	All		Mean	SD
Full Sample		4,918	0.052	0.427
By quarters				
2019 Q1	7,648,300	4,104	-0.026	0.503
2019 Q2	7,867,931	4,157	0.024	0.470
2019 Q3	6,626,285	4,149	0.042	0.438
2019 Q4	7,354,159	4,160	0.049	0.432
2020 Q1	8,391,080	4,155	0.013	0.418
2020 Q2	9,338,791	4,145	0.017	0.403
2020 Q3	11,816,515	4,153	0.036	0.399
2020 Q4	11,461,362	4,200	0.085	0.385
2021 Q1	11,800,767	4,316	0.109	0.388
2021 Q2	11,577,061	4,455	0.124	0.404
2021 Q3	9,592,437	4,534	0.131	0.401

Table 3. Top-20 Assets With The Highest Number Mentions in RMA and Comments In r/WSB

RMA			r/WSB		
Ticker	Name	Number of Mentions	Ticker	Name	Number of Comments
TSLA	Tesla Inc	6,719,764	GME	Gamestop Corp New	324,592
AMC	AMC Entertainment Holdings Inc	5,010,710	SPY	SPDR S&P 500 ETF Trust	297,243
AAPL	Apple Inc	3,517,540	TSLA	Tesla Inc	203,905
AMZN	Amazon Com Inc	2,736,730	AMC	AMC Entertainment Holdings Inc	183,392
GME	Gamestop Corp New	2,088,310	PLTR	Palantir Technologies Inc	137,763
NIO	NIO Inc	1,270,427	BB	Blackberry Ltd	137,723
BA	Boeing Co	1,206,104	AAPL	Apple Inc	97,026
MSFT	Microsoft Corp	1,098,436	AMD	Advanced Micro Devices Inc	93,730
AMD	Advanced Micro Devices Inc	1,086,395	NIO	NIO Inc	69,043
NFLX	Netflix Inc	894,194	MSFT	Microsoft Corp	60,786
SRNE	Sorrento Therapeutics Inc	822,574	RKT	Rocket Companies Inc	50,035
DIS	Disney Walt Co	805,231	NOK	Nokia Corp	49,045
PFE	Pfizer Inc	784,416	SPCE	Virgin Galactic Holdings Inc	48,711
WKHS	Workhorse Group Inc	762,677	BA	Boeing Co	47,412
IPOA	Social Cap Hedosophia Hldgs Corp	735,728	AMZN	Amazon Com Inc	47,348
BABA	Alibaba Group Holding Ltd	722,820	BABA	Alibaba Group Holding Ltd	42,357
ROKU	Roku Inc	691,966	CLOV	Clover Health Investments Corp	37,953
NVAX	Novavax Inc	660,337	FB	Facebook Inc	34,477
INO	Inovio Pharmaceuticals Inc	655,517	QQQ	Invesco QQQ Trust	33,028
FCEL	Fuelcell Energy Inc	642,607	DIS	Disney Walt Co	31,691

Table 4. Trader Characteristics

	All Traders	Social-Media Induced Traders	Regular Traders	χ^2 or T-Stat
Number of Traders	1,083,319	208,041	875,278	
Number of Trades	53,721,873	7,247,041	46,448,947	
Short Positions, %	6.49%	6.70%	6.43%	-
Leveraged Trades, %	26.92%	21.65%	27.76%	
Average Holding Days	12.99	9.03	13.62	
Female, %	12.85	12.61	12.91	t=3.7 (p<0.01)
Age Range, %				
18-24	16.31	21.38	15.11	
25-34	41.47	45.79	40.45	
35-44	25.69	21.38	26.72	χ^2=1.1e+04
45-54	11.31	7.95	12.11	(p<0.01)
55-64	4.13	2.78	4.46	
>65	0.90	0.60	0.98	
Trading Education, %				
No Financial Knowledge	41.86	43.67	41.43	
Trading Courses	34.74	34.02	34.91	χ^2=422.7
Degree or experience	12.52	12.28	12.57	(p<0.01)
Professional	10.87	10.02	11.07	
Trading Experience - Equities (past year), %				
Never traded	38.69	41.21	38.06	
0-10 times	31.95	33.34	31.61	χ^2=2.1e+03
10-20 times	11.99	11.45	12.12	(p<0.01)
Above 20 times	17.38	13.99	18.21	
Net Annual Income (USD), %				
Up to $10K	19.55	21.04	19.20	
$10K-$50K	47.55	47.61	47.54	
$50K-$200K	24.79	24.41	24.88	χ^2=736.4
$200K-$500K	2.92	2.50	3.02	(p<0.01)
$500K-$1M	1.65	1.41	1.70	
>$1M	3.53	3.03	3.65	
Primary Purpose of Trading, %				
Short Term Returns	19.65	22.58	18.96	
Additional Revenues	51.95	50.36	52.33	χ^2=1.5e+03
Future Planning	20.68	19.19	21.03	(p<0.01)
Saving For Home	7.72	7.88	7.68	
Preferred Risk-Reward Scenario, %				
Gain 5% / Lose -3%	3.35	3.48	3.32	
Gain 10% / Lose -6%	9.28	9.23	9.29	χ^2=47.1
Gain 20% / Lose -12%	26.99	26.49	27.11	(p<0.01)
Gain 40% / Lose -24%	34.46	34.61	34.43	
Gain 80% / Lose -48%	25.91	26.19	25.85	
Trading Strategy (Duration), %				
Short (Up to 24 Hours)	16.70	15.11	17.07	
Medium (Few Weeks to Months)	54.20	57.14	53.51	χ^2=769.2
Long (More Than Several Months)	29.10	27.75	29.42	(p<0.01)

Table 5. Attention Induced Trading and Retail Trading in the Platform: Sorting

This table reports average open-close imbalances (estimating equation (2) for stocks in relation to four attention-grabbing variables. In the first two columns, stocks are sorted into ten deciles by past-day returns and abnormal trading volume. In column 3, stocks are sorted into quintiles based on abnormal news article volume. In column 4, stocks with at least five mentions on social media are sorted into quintiles.

Source:	**CRSP**	**CRSP**		**RMA**	**r/WSB**
	1	**2**		**3**	**4**
Decile	$Return_{t-1}$	$Abnormal$ $TradingVolume_{t-1}$	*Quintile*	$Abnormal$ $News_{t-1}$	$Abnormal$ $SocialMedia_t$
1	0.0669	0.0134	Zero/Few	0.0255	-
2	0.0641	0.0250	1	0.0224	0.0358
3	0.0600	0.0331	2	0.0378	0.0221
4	0.0557	0.0442	3	0.0414	0.0322
5	0.0517	0.0513	4	0.0694	0.0475
6	0.0500	0.0524	5	0.1090	0.0716
7	0.0445	0.0560			
8	0.0354	0.0629			
9	0.0219	0.0592			
10	0.0296	0.0674			

Table 6. Attention Inducing Factors and Retail Trading in the Platform: Regression

This table reports the coefficient of standard OLS regressions from estimating equation (3). All specifications include stock and date effects. Standard errors are clustered at the stock and date levels and are in parentheses. *p<0.10, ** p<0.05, *** p<0.01.

Panel A: Open - Close Imbalance

Dependent Variable:	Open-Close Imbalance				
	(1)	(2)	(3)	(4)	(5)
Social Media Trade	0.070***				0.063***
	(0.005)				(0.005)
News Trade		0.004**			0.001
		(0.002)			(0.002)
Volume Trade			0.013***		0.007***
			(0.002)		(0.002)
Return Trade				0.012***	0.010***
				(0.002)	(0.003)
Date FE	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes
Observations	556,229	480,125	545,259	545,931	471,750
R^2	0.046	0.039	0.045	0.045	0.039

Panel B: Log Number of Open Trades

Dependent Variable:	Open-Close Imbalance				
	(1)	(2)	(3)	(4)	(5)
Social Media Trade	1.218***				1.003***
	(0.039)				(0.035)
News Trade		0.247***			0.135***
		(0.008)			(0.006)
Volume Trade			0.477***		0.381***
			(0.010)		(0.009)
Return Trade				0.445***	0.323***
				(0.011)	(0.011)
Date FE	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes
Observations	516,591	445,960	506,554	507,207	438,292
R^2	0.748	0.745	0.753	0.750	0.765

Table 7. Attention Inducing Factors and Retail Trading in the Market

This table reports OLS regression results. The dependent variable represents the ratio of total $USD traded by retail investors in a given stock divided by the total $USD traded by retail investors across all stocks in U.S. exchanges. All equations include the date and stock fixed effects. Standard errors are clustered at the stock and date levels and are in parentheses. *p<0.10, ** p<0.05, *** p<0.01.

Dependent Variable:	Retail Share		
	(1)	(2)	(3)
Social Media Trade	0.0024***	0.0023***	0.0022***
	(0.0002)	(0.0002)	(0.0002)
Return Trade		0.0001***	
		(0.0000)	
Volume Trade		0.0001***	
		(0.0000)	
News Trade		0.0000***	
		(0.0000)	
Log News			0.0000***
			(0.0000)
Return [t-2;t-1]			-0.0000
			(0.0000)
Return [t-5;t-2]			0.0000
			(0.0000)
Return [t-21;t-6]			0.0000*
			(0.0000)
Log Trading Volume			0.0002***
			(0.0000)
Date FE	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes
Observations	1,917,344	1,744,492	1,742,066
R^2	0.598	0.601	0.605

Table 8. Social Media-Induced Trading and Trade Returns

This table reports OLS regression results from estimating equation (4). The dependent variable is trade-level returns for stock s, traded on the day t, by an investor i. $SocialMediaTrade$ takes two forms - an indicator variable defined as in the equation (1) and a log number of mentions. $Trade\ Size$ - share of total equity balance of investor i invested to stock position s on the day t, $Short\ Position$ - indicator variable equal to one for short positions, $Leveraged\ Position$ - indicator variable equal to one for leveraged positions, $Holding\ Days$ - natural logarithm of the number of calendar days between open and close dates of the transaction. All equations include investor, stock, and date fixed effects. Standard errors are clustered at the stock and date levels and are in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Dependent Variable:	Trade-level Returns				
Social Media Trade Variable:	Indicator	Indicator	Log	Log	Indicator (Premarket)
	(1)	(2)	(3)	(4)	(5)
Social Media Trade	-0.0224***	-0.0161***	-0.0178***	-0.0172***	-0.0277***
	(0.0054)	(0.0059)	(0.0014)	(0.0014)	(0.0084)
News Trade		-0.0062*			-0.0046
		(0.0036)			(0.0036)
Volume Trade		-0.0085***			-0.0034
		(0.0028)			(0.0026)
Return Trade		-0.0082***			-0.0064**
		(0.0025)			(0.0025)
Trade Size, % of Account Balance			0.0040***	0.0031**	0.0018
			(0.0011)	(0.0013)	(0.0012)
Short Position			-0.0308***	-0.0309***	-0.0315***
			(0.0056)	(0.0057)	(0.0056)
Leveraged Position			-0.0068**	-0.0099***	-0.0049
			(0.0033)	(0.0032)	(0.0033)
Holding Days (Log)			0.0348***	0.0337***	0.0356***
			(0.0023)	(0.0023)	(0.0023)
Return [t-2;t-1]				-0.0811***	
				(0.0199)	
Return [t-5;t-2]				-0.0507***	
				(0.0065)	
Return [t-21;t-6]				-0.0147***	
				(0.0030)	
Trading Volume (Log)				0.0120***	
				(0.0034)	
News Volume (Log)			-0.0084***	-0.0054***	
			(0.0020)	(0.0016)	
Date FE	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes
Investor FE	Yes	Yes	Yes	Yes	Yes
Observations	46,298,502	42,951,475	42,960,549	41,845,930	42,951,475
R^2	0.120	0.125	0.144	0.147	0.140

Table 9. Attention Inducing Factors and Retail Trading in the Market

This table reports OLS regression results. The dependent variable represents the ratio of total $USD traded by retail investors in a given stock divided by the total $USD traded by retail investors across all stocks in U.S. exchanges. All equations include the date and stock fixed effects. Standard errors are clustered at the date level. Standard errors are clustered at the stock and date levels and are in parentheses. *p<0.10, ** p<0.05, *** p<0.01.

Dependent Variable:	Annualized Portfolio Returns		
	(1)	(2)	(3)
Social Media Trade %	-0.0172***	-0.0277***	-0.0280***
	(0.0009)	(0.0008)	(0.0008)
Log # of Positions	-0.0207***	-0.0084***	-0.0081***
	(0.0001)	(0.0001)	(0.0001)
Log # of Trading Months		0.0146***	0.0139***
		(0.0003)	(0.0003)
Crypto Trade %		0.0607***	0.0568***
		(0.0006)	(0.0007)
FX Trade %		-0.1394***	-0.1292***
		(0.0028)	(0.0028)
Commodity Trade %		-0.1417***	-0.1415***
		(0.0017)	(0.0017)
Index Trade %		-0.1071***	-0.1141***
		(0.0022)	(0.0022)
Leveraged Trade %		-0.0547***	-0.0525***
		(0.0008)	(0.0008)
Short Positions %		-0.1068***	-0.1057***
		(0.0015)	(0.0015)
Male			-0.0079***
			(0.0005)
Trading Knowledge			0.0008**
			(0.0003)
Age 18-24			-0.0168***
			(0.0015)
Age 25-34			-0.0107***
			(0.0015)
Age 35-44			-0.0083***
			(0.0015)
Age 45-54			-0.0074***
			(0.0015)
Age 55-64			-0.0045***
			(0.0016)
Observations	1,082,330	1,082,330	1,082,007
R^2	0.030	0.125	0.130

Table 10. Social Media Activity and Stock Returns

This table reports OLS regression results from estimating the equation (8). All equations include the date and stock fixed effects. Standard errors are clustered at the date and stock level. T-statistics are reported in brackets. * p<0.10, ** p<0.05, *** p<0.01.

Dependent Variable:	**Market-Adjusted Return**							
Period:	**[t]**	**[t;t+1]**	**[t;t+2]**	**[t;t+5]**	**[t;t+10]**	**[t;t+21]**	**[t;t+63]**	**[t;t+126]**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Social Media Trade	0.040***	-0.013***	-0.017***	-0.020**	-0.034***	-0.053***	-0.115***	-0.158***
	(2.897)	(-5.453)	(-5.515)	(-2.252)	(-2.981)	(-3.636)	(-4.381)	(-3.196)
Log (News Volume$_{t-1}$)	-0.002***	-0.002***	-0.002***	-0.002**	-0.002	-0.004	-0.008**	-0.015***
	(-5.978)	(-6.827)	(-5.210)	(-2.462)	(-1.066)	(-1.381)	(-2.362)	(-2.999)
Returns$_{t-1}$	-0.001	0.004	0.002	-0.004	-0.011***	-0.022***	-0.046***	-0.081***
	(-0.054)	(1.054)	(0.489)	(-1.039)	(-3.226)	(-6.201)	(-7.220)	(-4.631)
Returns$_{t-5;t-2}$	-0.011	0.000	-0.002	-0.007***	-0.015***	-0.026***	-0.052***	-0.090***
	(-0.883)	(0.153)	(-1.074)	(-5.118)	(-10.627)	(-9.189)	(-7.447)	(-4.405)
Returns$_{t-21;t-6}$	-0.002***	-0.002***	-0.004***	-0.011***	-0.020***	-0.036***	-0.072***	-0.126***
	(-5.502)	(-3.964)	(-7.951)	(-17.766)	(-12.350)	(-7.911)	(-7.098)	(-4.221)
Log (Trading Volume$_{t-1}$)	0.019***	0.014***	0.017***	0.024***	0.032***	0.042***	0.053**	0.065*
	(9.147)	(7.622)	(6.411)	(4.205)	(3.412)	(3.224)	(2.487)	(1.927)
Date FE	Y	Y	Y	Y	Y	Y	Y	Y
Stock FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	2,332,056	2,332,011	2,331,987	2,331,964	2,331,934	2,331,880	2,331,562	2,327,287
R-squared	0.015	0.012	0.011	0.013	0.021	0.038	0.099	0.154

Table 11. Disposition Effect

This table reports OLS regression results from estimating the equation (9). T-statistics are reported in brackets. * p<0.10, ** p<0.05, *** p<0.01.

Sample:	All	Non-Day Trades	Non-Leveraged Trades	Only Stocks
	(1)	(2)	(3)	(4)
Gain	0.021***	0.021***	0.022***	0.021***
	(11.261)	(10.423)	(13.602)	(10.208)
Social Media Trade	0.002	0.003*	0.004**	0.001
	(1.283)	(1.744)	(2.531)	(0.516)
Gain × Social Media Trade	0.006***	0.009***	0.007***	0.008***
	(3.097)	(4.506)	(3.981)	(4.092)
Observations	382,895,203	341,652,699	290,998,460	321,259,970
R-squared	0.002	0.002	0.003	0.002

Table 12. Social Media-Induced Traders and Returns from Other Asset Classes

This table reports OLS regression results from estimating the difference in trade-level returns of investors across asset classes. Each column is restricted to only equity, crypto, currency, and commodity trades. *Social Media Investor* variable equals one if the ratio of social media-induced trades from total trades falls into the top quintile among all investors in the platform. T-statistics are reported in brackets. * p<0.10, ** p<0.05, *** p<0.01.

Dependent Variable:	Trade-Level Returns				
Asset Class:	All	Equity	Crypto	Currency	Commodity
	(1)	(2)	(3)	(4)	(5)
Social Media Investor	-0.007***	-0.009***	-0.010*	-0.006***	-0.011***
	(-3.017)	(-3.512)	(-1.914)	(-5.331)	(-8.407)
Trade Size	-0.009***	-0.010***	-0.008**	-0.027***	-0.014***
	(-3.961)	(-3.142)	(-2.133)	(-15.030)	(-4.930)
Short Position	-0.020***	-0.021***	-0.046***	-0.006**	-0.014***
	(-4.248)	(-3.943)	(-3.920)	(-2.377)	(-2.943)
Leveraged Position	-0.010**	-0.007*	-0.023	-0.022***	-0.038***
	(-2.060)	(-1.676)	(-1.457)	(-9.562)	(-7.036)
Holding Days, Log	0.041***	0.031***	0.095***	-0.014***	0.001
	(5.607)	(6.167)	(5.065)	(-6.681)	(0.210)
Date FE	Y	Y	Y	Y	Y
Asset FE	Y	Y	Y	Y	Y
Observations	122,602,702	75,459,883	17,915,168	9,064,407	19,664,806
R-squared	0.062	0.049	0.164	0.009	0.018

Appendix

Other Attention Grabbing Factors

Barber and Odean (2008) found that retail investors display attention-driven trading behavior. Retail investors concentrate on buying stocks on high trading volume days, on days with both extremely negative and extremely positive one-day returns, and on days when stocks are in the news. We study how social media-induced attention trading relates to other attention-inducing factors - abnormal trading volume, past-day returns, and coverage of stock in the news.

News Coverage

Our data on the traditional news coverage also comes from Refinitiv's MarketPsych Analytics (RMA), which monitors all major news outlets (top 4,000 international business sources, top regional news sources, and leading industry sources), both print and online. Following a similar methodology to abnormal social media activity, we define abnormal news coverage for a stock s on the day t to be:

$$Abnormal\,News\,Coverage_{s,t} = \frac{News\,Mentions_{s,t}}{Average\,News\,Mentions_{s,[t-47;t-6]}}$$

Then, on the day t, we sort the abnormal news coverage variable for all stocks with at least two news articles to quintiles and define indicator variable $News\,Induced\,Trade$ equal to one if the stock's one day lagged abnormal news coverage variable falls in the top 20% and zero otherwise.

Trading Volume

Similarly to the social media activity measure, we calculate abnormal trading volume. On day t, we calculate the abnormal trading volume for stock s as a ratio of trading volume on the day t, as reported in CRSP, to an average trading volume through day $t-47$ to $t-6$. We use the lagged abnormal trading volume in our analysis and define the $VolumeInducedTrade$ indicator variable as equal to one if the stock's one-day lagged abnormal trading volume falls in the top 20% percentile on the day t.

Past Day Returns

When stocks have extreme daily returns, it is likely to get retail investors' attention, and we expect those retail investors to trade in response to both negative and positive price changes. To test this, we sort stocks into deciles based on the previous trading day's returns to account for the fact that many investors learn or react to prices after the market closes. On day t, we calculate the stock's return from day $t-2$ to $t-1$ and define the indicator variable $Return\,Induced\,Trade$ equal to one if a stock's absolute past day return is in the top 20% percentile.

Figure A1. Message rooms of r/WSB.

This figure shows a screenshot of r/WSB's thematic threads: Tomorrow's Moves and Daily Discussions. Source: Reddit

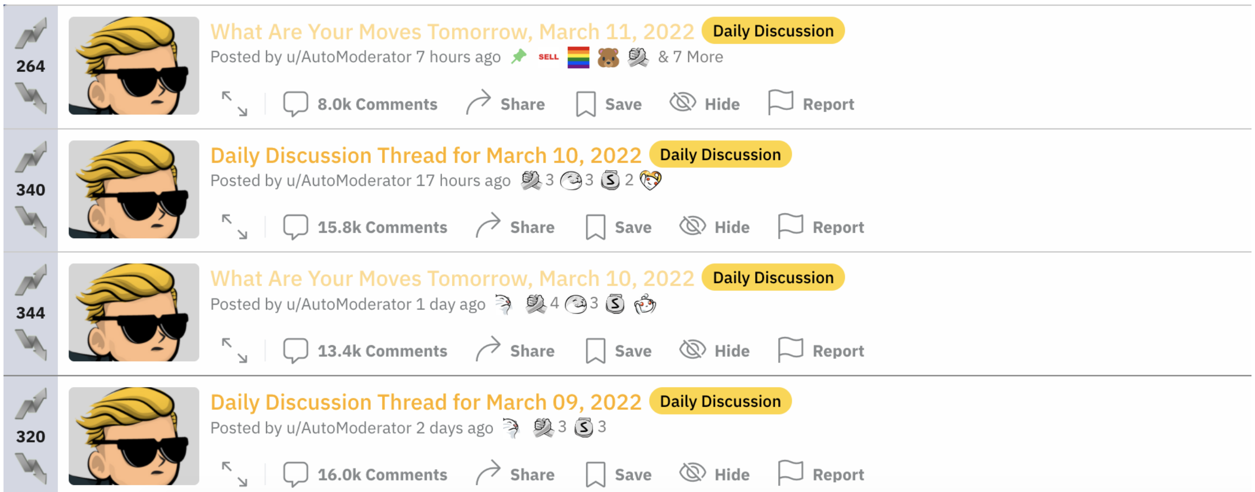


Figure A2. Distribution of comments in r/WSB by days and hours activity

This figure shows the distribution of comments in r/WSB by weekdays and by hours of the day. Source: Reddit

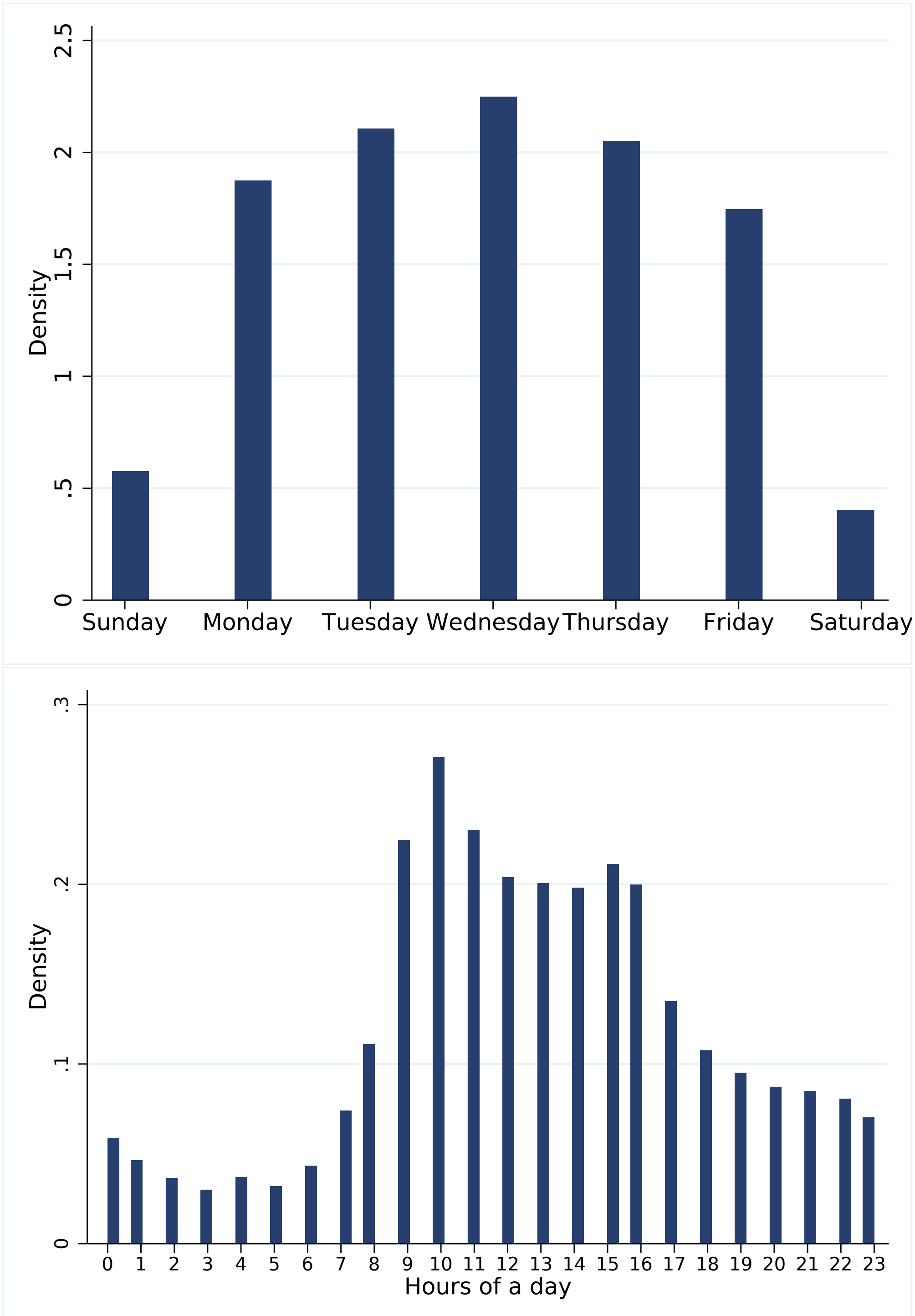


Figure A3. Daily activity in r/WSB.

This figure shows the daily total number of comments (upper panel) and the daily total number of mentioned stocks (lower panel) in r/WSB during the sample period. Source: Reddit